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Article Title: Downside risk and the size of credit spreads

Year of publication: 2011

Link to published article:
http://dx.doi.org/10.1016/j.jbankfin.2011.01.019

Downside risk and the size of credit spreads

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This version: 28 October 2010

Abstract

We investigate why spreads on corporate bonds are so much larger than expected losses from default. Systematic factors make very little contribution to spreads, even if higher moments or downside effects are taken into account. Instead we find that sizes of spreads are strongly related to idiosyncratic-risk factors: not only to idiosyncratic equity volatility, but even more to idiosyncratic bond volatility and idiosyncratic bond value-at-risk. Idiosyncratic bond volatility helps to explain spreads because it reflects not just the distribution of firm value but is also a proxy for liquidity risk. Idiosyncratic bond value-at-risk adds to this by capturing the left-skewness of the firm-value distribution. We confirm our results both for the initial 1997-2004 sample period and also out of sample for 2005-2009, which includes the sub-prime crisis. Overall, credit spreads are large because they incorporate a large risk premium related to investors' fears of extreme losses.

JEL classification: G12

Keywords: Bond; Idiosyncratic risk; Downside risk; Value-at-risk; Credit spread puzzle; Pricing kernel; Merton model; Liquidity; Sub-prime crisis

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1. Introduction

Many researchers have noted that spreads on corporate bonds are extremely large relative to their apparent risks. Spreads are larger than can be justified by expected losses from default (e.g., Elton et al., 2001) and larger than those generated by most option-based models which depend on the distribution of firm value (e.g., Eom, Helwege and Huang, 2004; Huang and Huang, 2003). This has become known as "the credit spread puzzle." It is particularly severe for bonds which have high ratings and short times to maturity.

The aim of our paper is to assess the extent to which measures of risk, derived from past equity and bond returns, can generate the credit spreads which are observed today. We use a sample of investment-grade corporate bonds observed weekly over 1998 to 2004 to answer this question and then confirm our results with an additional sample over 2005 to 2009, which includes the sub-prime crisis. Our focus is on explaining the sizes of spreads rather than just explaining their variances over time. In other words, we are more interested in economic relevance than in statistical significance, since in a sample as large as ours almost any variable is statistically significant but rather few are of economic importance.

We begin by examining the contribution of systematic risk and our first approach is the conventional one, which relates bond spreads to the three Fama/French systematic factors. Elton et al. (2001) suggest that these systematic risks – equity-market covariance, SMB and HML – may be important for bond spreads. These risks do explain some of the cross-sectional variance in our study, but their economic importance is minimal: together they generate just a few basis points of the median spread (of 111 basis points). Most studies to date have assumed that risk factors have a symmetric influence, but a few researchers have also suggested that spreads reflect the asymmetric returns which come from undiversifiable skewness in bond portfolios (Amato and Remolona, 2003, 2005). We therefore test whether higher moments – systematic co-skewness risk (Harvey and Siddique, 2000) or systematic downside covariance risk (Ang, Chen and Xing, 2006) – can explain observed spreads. Again we find that the effects are much too small to explain observed spreads. Consequently, we reach the conclusion that systematic risk factors, even with a downside focus, are weak candidates for directly explaining credit spreads.

Having dismissed systematic factors, we turn to the role of idiosyncratic factors in bond spreads. The theory of contingent claims (Merton, 1974) values a corporate bond as a risk-free bond less a deep-out-of-the-money put option on firm value. Based on this intuition, Campbell and Taksler (2003) show that idiosyncratic equity volatility (as a proxy for the volatility of firm value) has an important role in determining spreads. Extending this analysis, we examine two additional idiosyncratic bond return-based risk measures, namely idiosyncratic bond volatility and idiosyncratic bond value-at-risk. We find that both these risk measures contain additional information (beyond that in idiosyncratic equity volatility) that is relevant for determining credit spreads, and that idiosyncratic bond value-at-risk makes a larger economic contribution to spreads than does idiosyncratic bond volatility. Combining idiosyncratic value at risk with S&P volatility, we can explain up to 99 basis points (89%) of the median spread.

These results raise two questions. First, why does idiosyncratic bond volatility contain additional information to its equity counterpart in determining spreads? And second, why does idiosyncratic bond value-at-risk contain information not already captured by equity or bond volatility that is relevant to the size of spread? To answer the first question, we run regressions for data sorted into idiosyncratic-bond-volatility deciles and show that bonds with higher volatilities (and larger spreads) are also those which are more sensitive to changes in the level of liquidity. This suggests that bond volatility is a proxy for liquidity risk, with an impact large enough to generate a difference of 20 basis points in spreads between the top and bottom bond-volatility deciles.

We then address the second question, which concerns the information content of the idiosyncratic bond value-at-risk measure. Equity volatility and bond volatility are both proxies for the volatility of the risk-neutral distribution of firm value, whereas idiosyncratic bond value-at-risk captures not just the volatility of firm value but also its left-skewness. We would therefore like to know if the firm-value distribution is indeed left-skewed (in the risk-neutral domain), as that would be consistent with the importance of idiosyncratic bond value-at-risk to spreads. We test this conjecture in the following way. We take the estimated sensitivities of spreads to equity volatility for different levels of leverage (using deciles from our sample) and then use them to fit a structural model of the Merton type at each leverage level. (This approach to calibration circumvents the need to estimate firm volatility and does not appear to have been used before.) We demonstrate that the result from the data is an implied risk-neutral distribution for a representative firm which has a very fat left-hand tail. This is consistent with our hypothesis that idiosyncratic bond value-at-risk is able to generate realistic spreads because it takes into account the left-skewness of firm value in the risk-neutral domain.

While the paper was being finalized, the sub-prime crisis arrived and bond spreads increased hugely. We have therefore extended our original 1998-2004 sample to the period 2005-2009. This genuine out-of-sample test allows us to verify that bond volatility and bond value-at-risk remain important in determining spreads, both over the extremely quiet period of 2005-2006 and over the extremely turbulent period of 2007-2009.

The main contributions of our paper may be summarized as follows. First, we demonstrate that systematic risk has very little direct effect on the level of spreads, so the pricing of bonds cannot easily be related to the factors affecting the pricing of equities. Second, we show that idiosyncratic equity volatility has a larger impact on spreads, although not nearly as large as that found by Campbell and Taksler (2003). Third, we demonstrate that idiosyncratic bond volatility matters for spreads over and above the effect of idiosyncratic equity volatility, one reason being that it is a proxy for liquidity risk. Fourth, we find that idiosyncratic bond value-at-risk is the measure that generates the largest individual spreads, which is because it captures the long left-hand tail of the risk-neutral distribution of firm value. Fifth, we show that bond volatility and bond value-at-risk continue to be important determinants of spreads in the quiet period before the sub-prime crisis and in the turbulent period thereafter.

Our paper is related to several different strands in the existing literature. With respect to systematic risks, there has been surprisingly little work on whether conventional asset pricing models can explain either bond returns or bond spreads (notable exceptions being Fama and French (1993), Gebhardt, Hvidkjaer and Swaminathan (2004), and Elton, Gruber, Agrawal and Mann (2001)) and we try to fill this gap. Collin-Dufresne, Goldstein and Martin (2001) examine what determines changes in spreads rather than their size and conclude that there is a large unexplained component which is common across all bonds. Consistent with our paper, an implication of their research is that very little of the spread can be explained by the probability of default or by systematic factors.

Some researchers have investigated the extent to which liquidity could be the 'missing factor', but they are unable to explain more than about 20 basis points of the spread on investment-grade bonds (Ericsson and Renault, 2006; Perraudin and Taylor, 2004; Longstaff, Mithal and Neis, 2005; Chen, Lesmond and Wei, 2007; Bongaerts, de Jong and Driessen, 2008a). Acharya and Pedersen (2005) have argued that attention in asset pricing should be directed not only at the liquidity level but also at liquidity risk. Using the extended CAPM model of Acharya and Pedersen, Bongaerts, de Jong and Driessen, (2008b) suggest that more than half (about 60 basis points) of the spread on AA-rated bonds may be due to liquidity risk but Acharya, Amihud and Bharath (2008) find smaller values. This is not conclusive evidence because in these two studies liquidity is measured indirectly from treasury bonds and equities. A recent paper by Dick-Nielsen, Feldhuetter and Lando (2009) uses several different measures for liquidity level, together with the volatility of those measures as proxies for liquidity risk, to examine their potential contributions to spreads. They conclude that in normal times, such as before the sub-prime crisis (Q4/2004 to Q1/2007), liquidity level and risk could only account for 2-5 basis points of spread for investment-grade bonds, but that after the crisis in 2007, liquidity level and risk could account for a huge 64-116 basis points of spread.

The empirical paper which is closest to ours is by Campbell and Taksler (2003), who demonstrate that there is a strong positive relationship between idiosyncratic equity volatility and bond spreads. However, the spread/volatility relationship which they find is extraordinarily large, leading them to reject its consistency with structural models of the spread. Our view is that the structural approach to spreads is likely to be the correct one, even if the 'perfect' model remains unknown. This view is supported by Schaefer and Strebulaev (2008), who show that even a very simple Merton model is good for hedging of corporate bonds. Cremers, Driessen and Maenhout (2008) also show that contingent claims models can work. They construct a structural model with jumps that, when suitably calibrated, is capable of generating large credit spreads due to the presence of downside jump-risk premia. These downside jump-risk premia come through in our work in the form of the left-skewness in the risk-neutral distribution of firm value that we imply with our Merton-model calibration. [1]

Our paper is structured as follows. In Section 2 we describe the data, the risk variables and the control variables. Section 3 gives the results from testing systematic factors as generators of spreads. Section 4 analyzes the role of idiosyncratic risks in determining spreads and reveals empirically the importance of bond volatility and bond value-at-risk. Section 5 examines more precisely why bond volatility and bond value-at-risk are so important for the level of spreads. Section 6 extends the analysis to an out-of-sample period, 2005-2009. Finally, section 7 draws together the conclusions and implications of our study.

[1] Two other factors that affect spreads according to recent papers are information uncertainty/asymmetry (Lu, Chen and Liao, 2010; Guentay and Hackbarth, 2010) and time-varying market sentiment (Tang and Yan, 2010).

2. Data, risk variables and control variables

2.1. Sample details

The initial sample is based on the universe of US investment-grade corporate bonds contained within the Merrill Lynch Corporate Master index. We use data from Bloomberg at a weekly frequency over the 417-week period, January 1997 to November 2004. Bonds that are callable, puttable, or have features relating to conversion, sinking funds or step coupons are eliminated. We match the bond data with equity returns from the CRSP database. After removing outliers in the risk measures (based on three standard deviations) and data errors in the control variables, we are left with 125,837 usable bond-week observations.

We have chosen not to use a sample based on actual bond trades, such as the TRACE dataset, for two reasons. First, the TRACE dataset only became available for the full set of US corporate bonds from October 2004, limiting the useable length of time series. Second, our bond risk measures are calculated using weekly bond returns over a one-year window and a trade-based data set has gaps in return series for individual bonds, making it difficult to calculate those risk-measures. Using the Bloomberg data allows us to overcome this problem, as we have a continuous series with prices for each existing bond in each week.

Table I, Panel A, gives details of the bonds in the sample, classified by rating and by year. The numbers given in the table are for bonds which are "alive" at the beginning of each stated year. Whenever bonds reach maturity or new bonds are issued, the sample is adjusted and so there is no survivorship bias. The table shows that approximately 12% of the bonds have a rating of AA or AAA, 55% are A-rated and 33% are BBB-rated. Table I, Panel B, lists average spreads, by rating and by year. The numbers presented are annual time-series averages based on weekly cross-sections. Median spreads over the seven years range from 72 basis points for AAA bonds to 146 basis points for BBB bonds.

Figure 1 plots average spreads by rating over the sample period of 1997-2004. Lower grade bonds have consistently larger spreads, as would be expected, but all spreads tend to move together, rising from early 1997 to 2002 and then falling over the next two years. Four particular events lead to spikes in credit spreads during our sample period, as indicated in the figure: the LTCM crisis of 8/1998; the dot.com bubble on NASDAQ during 2000; the terrorist attack on the World Trade Center of 9/2001; and the WorldCom default of 6/2002.

2.2. Measures of bond risk

In this section we explain the general methodology and the measures of risk to be used in relating credit spreads to risk factors. In the first stage of our analysis we estimate the sensitivity of individual bond returns to risk factors in time series and in the second stage we then test whether the estimated factor-sensitivities can explain bond spreads using a panel approach. This is the familiar methodology of Fama and Macbeth (1973), except that in the second stage we use spreads as the dependent variable – which reflect promised future bond returns – rather than using actual, ex-post, bond returns.

Systematic risk is usually estimated for a given security by regressing its return in time-series on the return of a suitably chosen index. However a complicating factor in applying this to corporate bonds is that changes in the risk-free term structure may affect individual bonds differently from the way in which they affect the bond index. To remove the influence of changes in the risk-free term-structure, we calculate the duration of the index in each period and then calculate the return on a risk-free duration-matched portfolio of Treasury Bonds. We then subtract the duration-matched risk-free return from the return on the index in each week. The resulting series is an index of returns on the credit spread (designed specifically for the Merrill Lynch Corporate Master Index) and we call this the Return on the Systematic Credit Risk factor (*RSCR*).[2] To take account of the impact of changes in the riskless term structure on the returns of individual bonds, we deduct the appropriate risk-free return rf_{it} from each bond's return based on its duration. To estimate the simple beta for each bond, our first systematic risk measure, we estimate the following equation using 52 weeks of data:

$$RB_{it} - rf_{it} = a_{it} + \beta_{it}\,RSCR_t + e_{it} \quad (1).$$

As the bond beta captures the systematic risk of a bond, we measure the idiosyncratic volatility of the bond with the standard deviation of the residuals from equation (1).

To estimate whether size or value risks explain credit spreads, we extend equation (1) to include the familiar SIZE and HML factors (taken from Ken French's website), leading to the specification:

$$RB_{it} - rf_{it} = a_{it} + \beta_{it}\,RSCR_t + s_{it}SIZE_t + h_{it}HML_t + e_{it} \quad (2).$$

[2] The risk is systematic, because it is that which remains in a well-diversified portfolio of bonds.

Equations (1) and (2) consider the excess return on the bond index to be the "market" risk, but it might be argued that the excess return on the equity market is just as relevant. We therefore also estimate equation (2) replacing $RSCR_t$ with the excess return on the CRSP value-weighted index over three-month treasury bills, which gives us loadings on the three Fama/French factors for the case where the market factor is an equity index instead of a bond index. Elton, Gruber, Agrawal and Mann (2001) provide support for the role of these Fama/French equity-related factors in explaining credit spreads.

To test whether systematic higher-moment risk explains credit spreads we estimate systematic coskewness risk using the approach of Kraus and Litzenberger (1976) and Harvey and Siddique (2000). Applying this to bond-index risk we have,

$$RB_{it} - rf_{it} = a_{it} + \beta_{it}\, RSCR_t + \gamma_{it}\, RSCR_t^{\,2} + e_{it} \qquad (3),$$

where the systematic coskewness risk for bond *i* in week *t* is measured by γ_{it}.

Another potential measure of systematic risk is downside beta. Following Ang, Chen and Xing (2006), the downside beta of a security may be measured by estimating its sensitivity to the market return when the market is in a "down" state. We define "downside weeks" as those in which the gap widens between Moody's Seasoned Baa Corporate Bond Yield and the constant-maturity ten-year US government bond yield. These are weeks when credit conditions are worsening. We therefore measure downside and upside betas by partitioning the previous year's weekly observations into downside and upside weeks based on the above criteria and estimating equation (1).[3]

Investors may be more concerned with extreme downside returns, rather than with the simple downside returns which can be estimated with downside betas. We therefore also consider the systematic "tail risk" present in bond returns. To do this we estimate the total bond value-at-risk (with smoothing) and then partition it into components for systematic bond value-at-risk and idiosyncratic bond value-at-risk. We use the two largest percentage negative returns for a given bond during the previous 52 weeks, so the confidence level is 2/52 or 3.85%. The exact procedure is explained in the Appendix.[4] The larger and more negative is systematic bond value-at-risk, the more exposed is a bond to systematic tail risk and the larger the expected credit spread.

Table II presents the different systematic and idiosyncratic risk measures for our 1998-2004 bond sample, with averages for each rating in the left half of the table and values for the bottom, median and top deciles in the right half of the table. For some risk measures the anticipated relationship between risk and ratings can be seen, i.e. as bond rating declines the risk measure increases. However this tends not to happen as we move from AAA to AA ratings.[5] For AA, A and BBB ratings, bond betas (however they are measured) tend to increase as ratings decline. Systematic bond value-at-risk and idiosyncratic bond value-at-risk also rise as ratings decline, as do idiosyncratic bond volatility and equity volatility. On the other hand, the size (SMB) and

[3] Our downside betas are estimated using rolling annual windows. The minimum number of downside weeks within our 52-week windows ranges from 17 to 33, with a median of 24.

[4] The results are not materially affected by using smoothed value-at-risk rather than simple value-at-risk. The reason for smoothing the estimate is to avoid spurious jumps in value-at-risk when a large negative return in the period 52 weeks before the current week then drops out of the sample in the next week.

[5] The peculiarity of AAA bonds has also been noted by other researchers, including Elton et al (2001), Campbell and Taksler (2003) and Schaefer and Strebulaev (2007).

value (HML) risk factors do not show a clear pattern of variation across ratings.

Turning to the decile values in the right-hand part of the table, the range in risk measures between the bottom and top deciles is much wider than the range across ratings in the left-hand part of the table. For example, the bottom and top decile bond-index betas are -0.128 and +1.502 respectively, whereas the range across ratings in the left part of the table is only from 0.440 to 0.664. Similarly, the range over deciles for idiosyncratic equity volatility is from 19.2% to 44.7%, but the range over ratings is only from 27.5% to 33.6%. Averages of risk-measures for bonds within particular ratings are therefore bunched closely together and disguise the wider range of values which occur within each rating. An analysis which concentrates on bonds averaged by rating therefore overlooks a large part of the cross-sectional variation, as we shall see more precisely later.

2.3. Control variables

Apart from risk measures, several control variables are included in our regressions. These are split into *common* control variables that are the same for all bonds at each point in time and *bond-specific* control variables. The three *common control variables* are the level of the term structure (measured as the 5-year constant-maturity Treasury yield), the slope of the term structure (the gap between the 20-year and three-month constant-maturity Treasury yields), and the spread in yields between 30-day Eurodollar deposits and US Treasury bills. Consistent with structural models, the level of the term structure coefficient is expected to be negative. The slope of the term structure proxies for expectations about future interest rates (e.g. Campbell and Taksler, 2003; Collin-Dufresne et al, 2001) and is expected to have a negative coefficient. The

Eurodollar/Treasury difference in yields (TED), used by Campbell and Taksler (2003), is intended to capture the flight-to-quality that occurs when there is a financial crisis which manifests itself through the Eurodollar yield rising relative to the Treasury yield. It is expected to have a positive coefficient.

There are nine *bond-specific control variables* in the panel regressions: the reciprocal of the face value of the issue, the coupon rate, the time to maturity, five rating-related dummies and a dummy for financial companies. The reciprocal of the face value of the bond issue is used as a proxy for the level of liquidity and so is expected to have a positive coefficient. (The reciprocal is used, as it allows for a non-linear effect). The coupon rate affects the amount of tax to be paid or the attitudes of investors to payouts and is expected to have a positive coefficient. The time to maturity takes into account the shape of the term structure of credit spreads. The coefficient that we obtain on time to maturity in our panel regressions will depend on the mix of bonds in our sample, as high grade bonds will typically have a positive relationship between spread and maturity (as their ratings can only fall) while low-grade bonds are expected to have a negative relationship between spread and maturity (as their ratings can either rise or the bonds disappear from the sample). Turning to the five rating-related dummies, the first two of these correct for any change in rating between the time-series estimation of past risks and the current cross-section estimation of risk impacts. *Dummy Higher* (expected to be negative) takes a value of one in a given week's cross-section if a bond's rating one year ago was higher than its rating in the current week. *Dummy Lower* (expected to be positive) takes a value of one in a given cross-section if a bond's rating one year ago was lower than in the current cross-section. There is a need to control in cross-section for differences in expected losses due to default and we do this by including dummy variables for each of the three S&P ratings relative to AAA. Finally, we include a dummy variable for whether a bond is issued by a financial or by a non-financial company, as these firms may face different risks.

3. Results on systematic risks and bond spreads

In this section we examine how well the different systematic risk measures, estimated in the first stage in time-series up to the relevant week, explain current credit spreads in cross-section. We use pooled panel regressions and the dependent variable is the spread of each bond in each week of the sample period. We report robust t-values based on standard errors adjusted for clustering by issuer. [6]

On the left-hand side of Table III we give the estimated coefficients from the regressions and on the right-hand side of the table we give the contributions of the factors to the size of spread, i.e. their economic significance. We estimate the contribution of a variable by multiplying its coefficient by the range of that variable between its median and its smallest observed value in the sample or zero, whichever is the larger. For example, the median coupon in the sample is 7.125 and the minimum observed coupon 1.950, so the relevant coupon range is 7.125 – 1.950 = 5.075 and this is then multiplied by the estimated coefficient from the regression to give its contribution. Note that it would be a mistake to attribute to coupon the full 7.125 times the estimated regression coefficient, because the observed range of coupons does not extend to zero. We can be confident that the minimum value in the sample is a valid observation, as we have already removed outliers.

[6] We have also estimated our panel regressions with issuer and time fixed effects but these have little impact and hence we report our results without these fixed effects.

Beginning with the coefficients on the left-hand side of Table III, all five of the regressions explain about 31% of the variance. Regression 1 is the Fama/French specification using the bond index as the market factor in the first stage. This gives a positive and significant beta-risk coefficient of 11.4 and also positive and significant values for size-risk (27.8) and value-risk (22.6). The coefficients on inverse of face-value, coupon and time to maturity are also positive. The level and slope interest-rate variables at the bottom of the table have unexpected signs (positive and negative, respectively) and the TED (flight-to-quality) variable also has a negative coefficient which is implausible – it would imply that there are smaller spreads on corporate bonds when there is a flight to quality. The dummy variable for whether a company is financial or not, at the bottom of the table, suggests that on average such companies have about 8 basis points of extra spread.

Moving to the attributions for regression 1, shown in the first column on the right-hand side of the table, they are all very small. The Fama/French factors together contribute 5 basis points, all of this due to the contribution of the bond-index beta. The inverse-of-face-value variable generates 6 basis points, the coupon generates 20 basis points and time-to-maturity 7 basis points. So the three main control variables (i.e. those with the expected signs and which are statistically significant) together contribute another 33 basis points. These contributions can be compared with the sample median spread of 111 basis points.

Regression 2 is the Fama/French specification that uses an equity index as the market factor. It has a coefficient on the equity beta of 4.5 (not significant), a size coefficient of 54.0, and other coefficients which are similar to those already found for regression 1. The attributions indicate that the Fama/French factors in this case generate just 1 basis points of spread, less even than for the bond-index regression 1.

Regression 3 is the beta with co-skewness formulation. The coefficients on beta and gamma are both significant and contribute 5 and 0 basis points of spread respectively. Regression 4 uses the upside beta/downside beta specification. Both of these factors have significant coefficients and they contribute 1 and 4 basis points to spreads, respectively, which is similar to the beta/gamma formulation in regression 3. Finally, regression 5 uses the estimated "beta" on the systematic value-at-risk of a bond, which generates -1 basis points of spread. [7]

The message from Table III is that systematic risk has almost no impact on the median size of bond spread, even if a downside focus is included. We also find that there may be a liquidity effect (proxied by the inverse of face value) of about 6 basis points, a coupon effect of about 20 basis points, and a maturity effect of about 7 basis points. At best, using regression 3 which is the beta/gamma formulation, it is possible to explain 32% of the variance, while generating only 5 basis points of spread with risk factors and 33 basis points of spread with control factors. We now turn to idiosyncratic factors, to see if they are more successful in generating plausible spreads.

4. Results on idiosyncratic risks and bond spreads

To obtain a general idea of magnitudes, we begin in Figure 2 by plotting spreads against

[7] This result is different from the positive effect of value-at-risk on equity returns found by Bali, Demirtas and Levy (2009), but here we are considering only the (small) systematic component of that measure. Our results (later in the paper) on the impact of idiosyncratic value-at-risk for bond spreads are consistent with their findings for equity returns.

idiosyncratic equity volatility (Panel A) and idiosyncratic bond volatility (Panel B), using average values for each rating of bond in each week. It is immediately apparent from Panel A that spreads are strongly related to idiosyncratic equity volatility, as argued by Campbell and Taksler (2003). However, the relationship is non-linear, as would be expected from a Merton-style structural model. In Panel B of Figure 2, idiosyncratic bond volatility shows an even closer relationship to spreads than idiosyncratic equity volatility and its effect is also slightly non-linear. The simple correlations with spreads across the 125,837 bond weeks of the whole sample are +0.46 for idiosyncratic equity volatility and +0.51 for bond volatility. This preliminary evidence therefore indicates that the contribution of idiosyncratic volatility to spreads is likely to be larger than that of any systematic factor which has been found in Table III.

Table IV gives the results of panel regressions for individual bond spreads against idiosyncratic risks and control variables. The idiosyncratic risks considered are idiosyncratic equity volatility, idiosyncratic bond volatility, and idiosyncratic bond value-at-risk. To allow for the impact of market volatility (as contrasted with that of an individual firm), we also include in each regression the volatility of the S&P500 index over the last six months.[8] Another variable which we include, as suggested by Campbell and Taksler (2003), is the average daily S&P500 return over the last 180 days (in percent), as that may reflect either a change in leverage or a systematic movement in the risk-premium required by investors (see, for example, Barberis, Huang and Santos, 2001).

The regressions in Table IV explain between 41% and 54% of the variance of spreads, which is

[8] We use an exponentially weighted moving average estimate of the volatility of the S&P500. We have also experimented with using the VIX index of implied volatilities, but it is not significant when the S&P500 volatility is present and so we omit it from the table.

more than in Table III, and the majority of coefficients are statistically significant at the 1% level or better. Regression 6, which uses idiosyncratic equity volatility, explains 48% of the variance of spreads and has a slope on idiosyncratic equity volatility of 2.0 and on S&P volatility of 0.8. Together these can generate 50 basis points of the median sample spread of 111 basis points, as shown in the top section of the right-hand part of the table. A positive return on the S&P500 over the last six months also has a clear impact in reducing spreads: the coefficient of –187 indicates that a 10% per rise over the last 180 days would reduce spreads by 10.4 basis points (calculated as [10/180] x -187). The control variables for regression 6 have signs and magnitudes which are generally similar to those already found in Table III, except that the impact of the TED variable (expected to be positive) is now close to zero.

Regression 7 uses idiosyncratic bond volatility instead of idiosyncratic equity volatility. The results are similar to those in regression 6, except that the proportion of the variance which is explained rises to 52%. The slope coefficient on idiosyncratic bond volatility is 15.4 and on the S&P volatility remains significant at 0.8. Together S&P volatility and idiosyncratic bond volatility generate 73 basis points of spread (see right-hand part of the table), which is considerably more than S&P volatility and idiosyncratic equity volatility in regression 6. The control variables have signs and magnitudes which are similar to those in regression 6, with one exception: the coefficient on coupon is negative and not significantly different from zero, which makes it implausible as a tax effect (c.f. Elton et al, 2001; Qi, Liu and Wu (2010).

Regression 8 uses both idiosyncratic equity volatility and idiosyncratic bond volatility as explanatory variables. The result is that both volatilities have significant coefficients, with the bond slope being only slightly below its value in regression 7 (13.0 versus 15.4) and the equity slope falling somewhat relative to its value in equation 6 (1.2 versus 2.0). The proportion of variance explained rises a little to 54% and together the equity volatility, bond volatility and S&P volatility generate 88 basis points of spread which is 79% of the sample median spread.

Regression 9 uses idiosyncratic bond value-at-risk together with S&P volatility. The proportion of variance explained falls slightly to 47%, but the contribution of this new variable to the median spread is large, being 65 basis points. Together with S&P volatility in this regression it generates 74 basis points of spread, which is 66% of the sample median spread.

Regressions 6a, 7a, 8a and 9a repeat the specifications of regressions 6, 7, 8, and 9, but for reasons of parsimony we omit all of the control variables except two: the inverse of face-value (liquidity proxy) which has been shown to have a consistently positive impact in the previous regressions, and the dummy variable for financial companies. In regression 6a the idiosyncratic equity-volatility slope rises (relative to regression 6) to 2.4 and the S&P-volatility slope rises to 1.2. In regression 7a the idiosyncratic bond-volatility slope is virtually unchanged (from regression 7) at 15.1 and the S&P-volatility slope rises to 1.6. In regression 8a both idiosyncratic equity volatility and bond volatility remain significant, as well as S&P volatility; the proportion of the variance explained remains quite high at 52%. Finally, in regression 9a both idiosyncratic value-at-risk and S&P volatility remain significant. The contributions of risk variables to median spreads are 63 basis points for regression 6a, 79 basis points for regression 7a, 99 basis points for regression 8a, and also 99 basis points for regression 9a. These are respectively 57%, 71%, 89% and 89% of the median spread. In these parsimonious regressions, idiosyncratic bond value at risk alone can generate 84 basis points of spread (regression 9a), whereas idiosyncratic bond volatility generates 65 basis points (regression 7a) and idiosyncratic equity volatility generates 52 basis points (regression 6a).

The message from Table IV is that while idiosyncratic equity volatility and idiosyncratic bond volatility can generate quite large spreads, idiosyncratic bond value-at-risk (which incorporates skewness) has the most impressive contribution of all. In addition, there is a contribution to spreads of liquidity (proxied by the inverse of face value) of about 8 basis points in all of our regressions (equivalent to 7% of the median spread) and a similar contribution from the financial-company dummy. Our results differ qualitatively from those of Campbell and Taksler (2003), in that we discover the extra contributions of bond volatility and bond value-at-risk. They also differ quantitatively from those of Campbell and Taksler, in that we find the sensitivity of spreads to equity volatility to be 2.0 (in regression 6) whereas they report a value of about 12.[9] This difference is puzzling, but it appears that our magnitude is consistent with those found in several other recent studies of this relationship. [10]

To summarize, in this section we have found two interesting new results. Our first result is that idiosyncratic bond volatility contains information relevant for explaining the level of credit

[9] Campbell and Taksler (2003) Table II, Regression 4, has a coefficient on daily idiosyncratic equity volatility of 189.16, which, dividing by the square root of 250, is equivalent to 12.0 for annual idiosyncratic equity volatility.

[10] Other studies give values for the regression slope on equity volatility when spreads are used as the dependent variable that are much closer to the level of our paper than Campbell and Taksler (2003). The slope in Avramov, Jostova and Philipov (2007) is 2.69, it is 3.28 in Benkert (2004) using CDS premia, it is 0.95 in Bharath and Shumway (2008) when included with an expected default-frequency variable in the regression, and in Chen, Lesmond and Wei (2007) it is 3.44. One part of the explanation for Campbell and Taksler's result might be that they use daily transactions data, whereas other researchers use either quotes or weekly data (except for Benkert, who uses daily CDS premia). However, if we redo our analysis using bonds for weeks in which there is a change in the spread exceeding 5 basis points (in order to increase the probability that a transaction has occurred), the results are not materially affected. We also obtain similar results if we use: (i) total volatility rather than idiosyncratic volatility; or (ii) pure cross-sections (averaged across week), which should not be subject to any bias from infrequent trading.

spreads, which is additional to that contained in equity volatility. Our second result is that idiosyncratic bond value-at-risk contains more information relevant for the size of spread than either idiosyncratic equity volatility or idiosyncratic bond volatility and, together with other relevant variables, can generate spreads of realistic median size.

5. Why do idiosyncratic bond volatility and idiosyncratic bond value-at-risk help to explain the level of credit spreads?

The analysis so far has highlighted the role in explaining spreads not only of idiosyncratic equity volatility, but also of idiosyncratic bond volatility and idiosyncratic bond value-at-risk. In this section we examine why this may be happening.

5.1. The role of idiosyncratic bond volatility

Two possible reasons for the impact of idiosyncratic bond volatility in cross-section might be: (i) that idiosyncratic bond volatility reflects ratings, which have residual effects on spreads; or (ii) that idiosyncratic bond volatility is a proxy for liquidity or liquidity risk, which commands a premium. Considering the first possibility, idiosyncratic bond volatility has quite a narrow variation across ratings, from an average of 5.88 for AAA bonds to 6.54 for BBB bonds (see Table II). If we sort the sample into deciles based on idiosyncratic bond volatility, we find that the range in such volatility across deciles is much wider, from 3.77 to 10.22, as shown in column (2) of Table V. Therefore idiosyncratic bond volatility is not closely related to ratings, so ratings cannot explain why idiosyncratic bond volatility matters for spreads in cross-section.

Considering the second possibility, if idiosyncratic bond volatility is a measure of liquidity risk then we would expect to find that investors become more sensitive to liquidity as we move up the idiosyncratic bond-volatility deciles. To test this hypothesis we estimate a new panel regression between spreads and idiosyncratic equity volatility, with the same variables as already used in regression 6a, but this time we use dummy variables to allow each bond-volatility decile to have its own coefficient on the liquidity proxy (inverse of face-value) and its own coefficient on idiosyncratic equity volatility[11]. The results by decile for the coefficients on the liquidity proxy are given in column 3 of Table V. The coefficients rise almost monotonically (from 471 to 5944) as we move up idiosyncratic-bond-volatility deciles, which implies that spreads are more sensitive to liquidity for bonds which have more idiosyncratic volatility. This result could be caused by the size of bond issue becoming smaller (liquidity falling) as we go up the bond-volatility deciles, but column (4) of Table V shows that this does not happen: there is no relationship between face value and idiosyncratic bond volatility. So we can conclude that one reason why idiosyncratic bond volatility is important for spreads is as a measure of liquidity risk. Using the coefficients in column (3) and the mean face values in column (4), we can calculate the liquidity premium for each decile, which is given in column (6). It shows that bonds in the lowest idiosyncratic volatility decile have a liquidity premium of (471/301=) 1.6 basis points, whereas bonds in the highest idiosyncratic volatility decile have a liquidity premium of (5944/270=) 22 basis points. The premium on liquidity risk between the top and bottom idiosyncratic-bond-volatility deciles is therefore approximately 20 basis points.

[11] We have also excluded the financial dummy in these regressions.

5.2. The role of idiosyncratic bond value-at-risk

We now turn to the question of why idiosyncratic bond value-at-risk can explain such a large proportion of the size of credit spreads. Our hypothesis is that bond value-at-risk reflects the downside skewness (or left-tail properties) of the risk-neutral distribution of firm value. If that distribution is highly skewed, then even extremely safe AAA-rated bonds could have significant credit spreads, which might explain the median spread of 72 basis points for AAA bonds in our sample.

How can we show that the risk neutral distribution of firm value is left-skewed? The intuition behind the method that we use is the following. A corporate bond is equivalent to a risk-free bond plus a short position in a put written on firm value, the latter having a strike which reflects the outstanding debt of the firm. Bonds written by firms with lower leverage have put components with strikes way out-of-the-money and therefore have implied volatilities reflecting the mass of the risk-neutral distribution of firm value in its far left tail. For example, the AAA bonds for non-financial companies in our sample have a median leverage of 4%, i.e. the median AAA put is 96% out-of-the-money. In contrast, bonds written by firms with higher leverage have put components with strikes much closer to-the-money and implied volatilities reflecting the mass of the risk-neutral firm-value distribution much closer to the current firm value. For example, the BBB bonds for non-financial companies in our sample have a median leverage of 36%, i.e. the median BBB put is only 64% out-of-the-money. Therefore by comparing the implied volatilities of firms with low and high leverage we can understand the shape of the risk-neutral distribution of firm value as we move out towards its lower tail.

We begin by forming leverage deciles from our sample. The data on leverage are obtained from CRSP and we focus on non-financial companies, leaving a sample of 82,762 bond weeks.[12] We then calibrate a Merton model to a representative bond within each of these ten leverage deciles, using median values from the sample. Instead of imposing a particular volatility or implying the volatility from the observed spreads, which would be the conventional approach, we calibrate the model to the estimated spread/equity-volatility sensitivity for each leverage decile.

To the best of our knowledge this procedure for calibration has not been used before.[13] If there is a high degree of left-skewness in the risk-neutral distribution, then the spread/equity-volatility sensitivities will reveal this via the calibrated model in the form of implied volatilities which are large and diminishing with leverage. To implement the Merton model we make two assumptions: (i) we assume that a coupon-paying bond is equivalent to a zero-coupon bond with the same duration and so we set the bond maturity to be equal to its duration; and (ii) we assume that the firm's leverage ratio will have reverted fully to its mean (estimated over the seven-year sample period) by the time the bond matures, which is similar to the approach taken by Collin-Dufresne and Goldstein (2001).[14]

Table VI gives (by leverage decile) both the information used for calibration and the results from the model. The leverage in the sample (column 2) ranges from 5.5% in decile 1 to 61.2% in decile 10. The duration of the bonds does not vary much across deciles, being about 6 for all of them (as shown in column 3). The sensitivity of spreads to total equity volatility, estimated from

[12] Leverage for financial companies is different, because the nature of their business is based on leverage.
[13] Campbell and Taklser (2003) note that their estimated sensitivities are implausibly large for a structural model to work.
[14] We also assume that there is a flat term structure at a rate of 5% per annum. With respect to the pay-out rate on the firm's assets, it has no effect on spreads in this particular model because the leverage ratio is assumed to be at the sample mean at bond maturity.

the panel, is given in column 4; it ranges from 2.56 to 4.11.[15] Column 5 gives the main result: the firm-value volatility from the Merton model for a representative firm in each leverage decile, derived from the sensitivity of spreads to equity volatility in column 4.[16] As can be seen, the implied volatilities for firm value show a steep and monotonic decline as leverage rises, from 46.9% for firms with the lowest leverage to 16.4% for firms with the highest leverage.

When these implied volatilities for firm value are plotted against leverage, as is done in the lower line of Figure 3, they generate a "volatility sneer" which is reminiscent of that found from studies of equity-index options. If there were no left-skewness in the risk-neutral distribution of firm value, then these volatilities would not differ across leverage and the lower line in Figure 3 would be horizontal. As we move up the leverage deciles, we are valuing put options in the Merton model which are progressively more out-of-the money: bonds in tenth decile have a leverage of 61% and so their put options are only 39% out-of-the-money; bonds in the first decile have a leverage of 6% and so their put options are 94% out-of-the-money. The increasing slope of the volatility smile, which is found as we move from high to low leverage, indicates a fat left-hand tail in the risk-neutral distribution of firm value.

Column 6 of Table VI gives the calculated equity volatilities that are consistent with the firm-value volatilities in the previous column.[17] These equity volatilities are also plotted against leverage as the upper line in Figure 3 and show that there is much less of an 'implied sneer' in

[15] The reported regression slope for the sample of bonds in a given rating is the sum of slopes for the individual equity volatility and for the S&P volatility, in the same way as reported for individual bonds in Table IV.
[16] We use a numerical procedure to find the results, changing the volatility of firm value until it is consistent with the given sensitivity of the spread to equity volatility.
[17] Ito's lemma connects stock volatility (σ_s) and firm volatility (σ_v) : $\sigma_s = \sigma_v \frac{V}{S} \frac{\partial S}{\partial V}$ where $\frac{\partial S}{\partial V}$ is estimated with the model, V denotes firm value and S denotes equity.

equity volatility than there is in firm-value volatility. That is consistent with the evidence of research on the smiles of options on individual equities, which do not generally show a sneer but show quite a wide variety of shapes (see Bakshi, Kapadia and Madan, 2003; Buraschi, Trojani and Vedolin, 2009). Column 7 of Table VI gives the spreads generated by the model, which range from 14 basis points in the second decile to 50 basis points in the tenth decile. Comparing these model spreads with the market spreads, given in column 8, we find that the model is able to generate about 15- 30% of observed spreads. These modest spreads, generated by calibrating the model to the spread/equity-volatility sensitivity, are nevertheless much larger than those which are generated by using the conventional approach (in which the volatility of firm value is estimated from observed equity volatility), particularly for the safest bonds. The latter approach generates only 2 basis points of spread for the first four leverage levels, as compared with the new approach which generates 14-17 basis points for the same leverages. [18]

We can now summarize what has been learnt from the calibration exercise with the Merton model from our panel data. [19] It shows that the risk-neutral distribution of firm value is left-skewed, which increases the value of out-of-the-money put options relative to a lognormal world and "pumps up" the spreads on the lower-leverage AAA and AA bonds. The observed risk-neutral skewness is consistent with the hypothesis made at the beginning of this section, that idiosyncratic bond value-at-risk generates large spreads because it captures left-skewness in the risk-neutral domain.[20]

[18] The conventional approach is to estimate the volatility of firm value from equity volatility and then solve simultaneously for the firm-value volatility and firm value. Schaefer and Strebulaev (2008) give a clear discussion of this method. We omit detailed calculations here, for reasons of space and continuity.

[19] We have experimented with fitting the Merton model directly to the spread/ idiosyncratic bond value-at-risk sensitivity. This does not work satisfactorily because more than one solution is possible. In this regard, it is well known that value-at-risk is not a coherent measure (Artzner, Delbaen, Eber and Heath, 1999).

[20] The conclusion that there is left-skewness in the risk-neutral distribution is consistent with the structural approach of Cremers

6. Out-of-sample tests over 2005-2006 and 2007-2009

The paper so far has used data up to the end of 2004, but the years immediately following are particularly interesting as 2005-2006 is a period of benign markets and low spreads, whereas 2007-2009 is the period of the sub-prime crisis and has volatile markets and high spreads. We have therefore collected a new set of data for 2005-2009 in order to test how well our different measures of idiosyncratic risk perform across changing bond market conditions.[21] This constitutes a genuine out-of-sample test of our risk measures as we did not have this data to hand when our paper was initially written. The new data were collected and cleaned in the same manner as for our initial sample and after removal of outliers we were left with 163,158 additional bond-week observations.

Figure 4 plots spreads for A-rated bonds, together with S&P500 volatility, over the whole 1998-2009 period.[22] During 2005-2006 S&P500 volatility is at the low average level of 11.8% and A-rated spreads are also low, averaging 85 basis points. During 2007 both volatility and spreads start to rise and the peak in spreads comes in December 2008, when A-rated spreads reach 642 basis points. Given the two distinct periods in the new sample, we re-run our idiosyncratic-risk regressions for both the quiet 2005-2006 period and for the extremely volatile sub-prime crisis period 2007-2009.

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et al (2008) and the reduced-form approaches of Berndt, Duffie, Ferguson and Schranz (2008) and Driessen (2005).

[21] We thank the referee for suggesting this extension of our original study. Our new sample follows on exactly from the previous sample and starts in December 2004.

[22] We plot A-rated bonds, as they are the largest group in our sample, but other rating groups behave similarly.

Table VII gives the results of the idiosyncratic-risk regressions for the quiet period of 2005-2006, in the format already used for the period 1998-2004 in Table IV. The median spread in this period is 66 basis points. Looking at the attributions in the right-hand part of the table, idiosyncratic equity volatility and S&P volatility have almost no influence on spreads in this period, which contrasts with our earlier finding that idiosyncratic equity volatility is important for 1998-2004. How can we interpret the low contribution of these types of equity volatility to spreads during 2005-2006? If we step back and consider the relationship between spreads and equity volatility from a structural model perspective, the relationship is non-linear and increasing in slope. As a result, equity volatility will only have a telling impact on spreads if it is sufficiently high which was not the case during 2005-2006. Hence it is perfectly plausible that the contributions of equity volatility and S&P 500 volatility during this period are close to zero.

Interestingly, Table VII also shows that idiosyncratic bond volatility remains just as important over 2005-2006 as before, contributing up to 50 basis points of spread and that idiosyncratic value-at-risk can also generate 38 basis points of spread. These contributions are quite large when compared with the 66 basis-point median spread in this two-year period and are 75% and 58% of the median spread respectively. The results for 2005-2006 therefore support idiosyncratic bond volatility and idiosyncratic bond value-at-risk as major contributors to the level of spreads, even in a remarkably quiet period.

The period 2007-2009 is completely different from 2005-2006, because it includes the sub-prime crisis, and the median spread is nearly three times as large, being 190 basis points. The regression results for this period are given in Table VIII. Once again looking at the attributions in the right-hand part of the table, we see that idiosyncratic bond value-at-risk now makes the largest contribution to spreads of up to 111 basis points. This may be compared with the contribution of up to 58 basis points for idiosyncratic bond volatility and the contribution of up to 57 basis points for idiosyncratic equity volatility. At the same time, S&P 500 volatility also becomes much more important than it was over 1998-2004, with a contribution that reaches 65 basis points (depending on which other variables are included in the regression). What explains the greater importance of S&P 500 and idiosyncratic equity volatility during the sub-prime period? Again this stems from the non-linear relationship between spreads and equity volatility as equity volatility will only contribute to spreads if it is sufficiently high. This was the case during the sub-prime episode which explains why both types of equity volatility in 2007-2009 make a more substantial contribution to spreads.

The median spread over this period is 190 basis points, so idiosyncratic bond value-at-risk can generate nearly 60% of the spread while the idiosyncratic measures based on bond volatility and idiosyncratic equity volatility can each generate about 30% of the spread. In addition, S&P 500 volatility contributes up to 59% of the spread, which is a sharp contrast to its zero contribution over 2005-2006. Together idiosyncratic value at risk and S&P 500 volatility can generate up to 175 basis points of spread, which is 92% of the median.

One other variable which increases its influence in 2007-2009 is whether a company is financial or not. During the sub-prime period of 2007-2009 being a financial company leads to a spread which is on average about 80 basis points larger than that of an equivalent non-financial company, after all other factors have been taken into account. This may be compared with its impact over 2005-2006 of close to zero (Table VII) and of about 10 basis points over 1998-2004 (Table IV).

In conclusion, extending the sample to 2005-2006 and 2007-2009 confirms that idiosyncratic bond volatility and idiosyncratic bond value-at-risk are closely related to the size of spread on corporate bonds. [23] They are important not only in an extremely volatile period (2007-2009) but also in an extremely quiet period (2005-2006). It appears that idiosyncratic bond volatility has a relatively constant impact in all periods, whereas idiosyncratic bond value at risk rises and falls in its relative importance for spreads as the market volatility rises and falls. The conclusions from the earlier 1998-2004 period on the importance of these variables for spreads are therefore strongly supported by these out-of-sample tests.

7. Conclusions and implications

Our paper investigates why credit-spreads for investment-grade corporate bonds are so large. We find that over 1998-2004 systematic risk factors can explain some of the variance of spreads but make very little contribution to their level. Instead we find that the level of spreads is related more closely to idiosyncratic risk, not only to idiosyncratic equity volatility (as in

[23] We have also checked that idiosyncratic bond volatility and idiosyncratic bond value-at-risk remain important for explaining the size of spreads for the full period December 2004 to December 2009 inclusive. Idiosyncratic bond value-at-risk makes the largest contribution to median bond spreads (which were approximately 100 basis points) over this period of 91 basis points, followed by idiosyncratic bond volatility with a contribution of 46 basis points and then by idiosyncratic equity volatility with a contribution of 34 basis points (all at best). S&P volatility also contributes upto 40 basis points to spreads. Undertaking our tests for the two separate periods 2005-2006 and for 2007-2009 constitutes a much more severe test of our idiosyncratic risk variables as we are effectively undertaking two rather than simply one out-of-sample test.

Campbell and Taksler, 2003), but also to idiosyncratic bond volatility and idiosyncratic bond value-at-risk. Of these risk measures, idiosyncratic bond volatility has the highest correlation with spreads, but idiosyncratic bond value-at-risk generates the largest spreads. Idiosyncratic risks (including that of a bond and of the S&P500) can explain up to 90% of the size of spread and about half of its variance. During the quiet period before the sub-prime crisis of 2005-2006, idiosyncratic equity volatility becomes unimportant for spreads but the bond-based risk measures do not. After the sub-prime crisis over 2007-2009, all idiosyncratic risk measures become more important for the level of spreads, but particularly idiosyncratic value at risk.

This raises the question of why idiosyncratic bond volatility and idiosyncratic bond value-at-risk are relevant to spreads. We find that idiosyncratic bond volatility is not just an indicator of the volatility of firm value, but it also reflects liquidity risk. After removing the effect of equity volatility, bonds with higher idiosyncratic volatility over 1998-2004 are more sensitive to the level of liquidity (as proxied by the inverse of issue size). The differences in liquidity risk measured in this way across individual bonds in our sample are quite large, generating 20 basis points of extra spread between the top and bottom bond-volatility deciles. By contrast, the differences in liquidity risk across ratings are quite small (because each rating is a mix of both high-liquidity and low-liquidity bonds), so using a bond's rating as a measure of its liquidity risk could be misleading.

We hypothesize that idiosyncratic bond value-at-risk generates large spreads because it allows for left-skewness of the distribution of firm value (in the risk-neutral domain). We therefore test whether the firm-value distribution (in the risk-neutral domain) is indeed left-skewed. By calibrating a Merton-style structural model in a new way, using the sensitivity of spreads to equity volatility from our sample, we are able to show that the left tail of the firm-value distribution is extremely fat relative to the lognormal standard. The implication is that investors exhibit great aversion to extreme losses, which is consistent with the effectiveness of idiosyncratic bond value-at-risk in generating large spreads. We also find that this effect falls in the quiet period of 2005-2006 and rises in the volatile sub-prime period of 2007-2009.

Our work has several implications for future research. First, our results support the option-based (structural) approach to credit spreads, but they also suggest that such models will not be very successful unless they take account of investors' extreme aversion to risk on the downside. The model by Leland (2006) is a move in that direction. Second, more research is needed on liquidity risk and bond spreads. This work should not only report on the statistical significance of regression models but also on its economic significance, i.e. the model's ability to generate spreads of a plausible size, as we have done. We need to understand better the way in which investors perceive bond volatility as a measure of liquidity risk and why bond volatility is so huge (see also Bao and Pan, 2008). The 'credit crunch' data from the middle of 2007 onwards provide an ideal sample for such analyses. Credit-crunch research to date has concentrated more on potential mechanisms for liquidity-feedback loops than on the exact nature of liquidity (see e.g. Brunnermeier and Pedersen, 2009, with an exception being Dick-Nielsen et al, 2009). Third, it would be interesting to see how well the forward-looking risk premium from bond spreads is able to predict the risk premium in the stock market. The equity risk-premium puzzle and bond credit-spread puzzle seem likely to be one and the same, as argued by Chen, Collin-Dufresne and Goldstein (2006): both depend on time-varying risk-aversion and a left-skewed risk-neutral distribution of firm value. Some initial work along these lines, based on the similarity of the behaviour of equity-index options and bond credit spreads, has been completed by Gemmill and Yang (2009) and such a view also underlies the analysis of CDO mispricing by Coval, Jurek and Stafford (2009).

Acknowledgments

We thank Ronald Anderson, Peter Christoffersen, Keith Cuthbertson, Darrell Duffie, Joost Driessen, Miguel Ferreira, Ian Marsh, Kjell Nyborg, Richard Payne, Pedro Santa-Clara, David Stolin, Suresh Sundaresan, Alex Taylor, Lorenzo Trapani and seminar participants at Athens University of Business and Economics, Bologna University, Cass Business School, the European Winter Finance Summit at Skarsnuten in Norway, HEC Lausanne, ISCTE Lisbon, Manchester Business School, Toulouse Business School, University of Bristol and Warwick Business School. We also thank JingFeng Ahn and Myria Kyriakou for data assistance and an anonymous referee for helpful suggestions. All errors and omissions are ours.

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Appendix: Estimating weekly bond value-at-risk

In this appendix we describe how we estimate our smoothed bond value-at-risk measures. The procedure we use involves estimating value-at-risk using data from the last 52 weeks, based on the two weeks for which weighted returns are lowest. We take bond returns over the last 52 weeks and weight them more heavily if they are recent. We weight each return as:

$$RW_t = R_{t-k}\,[(52-k)/52]^{\lambda},$$

where RW is weighted return, R is unweighted return, k is an index of weeks (in the range 0 to 52), t denotes current week and λ is a parameter (for which we choose the value 0.1).

Let the largest negative weighted return over 52 weeks be RW_{t1}. This is used as one estimate of value-at-risk. To split this value-at-risk into systematic and idiosyncratic components, we use the remaining 51 weeks of data to run equation (1). We then find the systematic component by using the estimated beta from equation (1), together with the values of the other independent variables in the value-at-risk week. The residual is the idiosyncratic value-at-risk.

We repeat this process with the 51 weeks of weighted returns, excluding RW_{t1}, and find the week with the second-highest value-at-risk, RW_{t2}. This is then split into its systematic and idiosyncratic components, as was done with RW_{t1}.

Finally, we average the two systematic values-at-risk and the two idiosyncratic values-at-risk, to give the final smoothed estimates of systematic value-at-risk and idiosyncratic value-at-risk.

Table I: Details of the 1998-2004 Bond Sample

This table presents details of our sample. The numbers of bonds in Panel A are for bonds which are "alive" at the beginning of each stated year in each rating category. Average spreads by rating in Panel B are calculated as annual time series averages based on weekly cross-sections. Mean and median bond market value, coupon rate, time to maturity, duration and leverage across bond-weeks by rating are presented in Panel C. Leverage is measured for non-financial companies only.

Panel A: Number of Bonds in Sample, by Rating Year

Rating	1998	1999	2000	2001	2002	2003	2004	Across years	
								Mean	Proportion
AAA	15	15	18	15	13	19	19	16	3.5%
AA	48	57	53	47	48	41	32	47	9.9%
A	230	266	270	260	233	250	253	252	53.4%
BBB	134	153	167	164	156	147	178	157	33.3%
All bonds	427	491	508	486	450	457	482	472	100.0%

Panel B: Average Bond Spreads by Rating Year (basis points)

Rating	1998	1999	2000	2001	2002	2003	2004	Across years	
								Mean	Median
AAA	57.4	73.4	106.0	94.2	85.0	62.3	53.2	74.3	72.0
AA	68.8	76.1	115.6	101.3	87.3	64.8	50.7	83.4	77.0
A	91.7	104.8	153.4	144.3	121.7	84.4	67.3	109.7	103.0
BBB	126.1	153.3	207.3	204.5	195.2	144.9	114.1	163.8	146.0
All bonds	97.5	115.9	165.1	157.1	139.7	100.7	81.8	122.9	111.0

Panel C: Characteristics of Bond Sample by Rating

Characteristic	AAA		AA		A		BBB	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Face value ($m)	313.2	300	319	250	281.7	250	291.8	250
Coupon rate (%)	6.9	6.8	7.0	6.8	7.2	7.1	7.4	7.3
Maturity (years)	15.2	10.4	10.2	7.0	10.5	7.2	10.5	7.2
Duration (years)	8.4	7.6	6.4	5.6	6.4	5.7	6.3	5.7
Leverage (%)	11.9	4.3	15.5	12.0	27.8	23.4	37.7	36.6

Table II: Bond Risk Measures for 1998-2004 Averaged by Rating and by Decile

This table gives average values, for ratings and for top, bottom and middle deciles of the risk measures used in the two-stage asset-pricing tests. Beta (bond index) is estimated by regressing bond returns in excess of a matched risk-free bond return on the systematic credit risk factor while the beta (equity index) is estimated by regressing the same excess bond return on the excess return on the CRSP value-weighted index. FF denotes the Fama/French three-factor model. SMB is the coefficient on the Fama/French size factor. HML is coefficient on the Fama/French value factor. Gamma is the coefficient on the systematic credit risk factor squared and measures co-skewness. Beta upside and beta downside are betas estimated using a bond index for data separated into up and down periods. Value-at-risk is measured as described in the main text and the Appendix.

Risk Measure	AAA	AA	A	BBB	Bottom Decile	Median	Top Decile
Beta (bond index)	0.440	0.413	0.575	0.664	-0.128	0.461	1.502
Beta (FF, bond index)	0.424	0.403	0.563	0.651	-0.163	0.450	1.500
SMB (FF, bond index)	0.014	0.011	0.012	0.008	-0.097	0.007	0.124
HML (FF, bond index)	0.017	0.016	0.010	0.004	-0.114	0.004	0.132
Beta (FF, equity index)	0.005	0.006	0.008	0.011	-0.083	0.007	0.100
SMB (FF, equity index)	0.023	0.026	0.029	0.026	-0.100	0.019	0.164
HML (FF, equity index)	0.018	0.024	0.021	0.017	-0.133	0.015	0.181
Beta (co-skewness)	0.260	0.307	0.488	0.576	-0.310	0.374	1.478
Gamma (co-skewness)	-12.790	-4.010	-5.220	-2.770	-120.190	-2.680	120.052
Beta downside (bond index)	0.599	0.490	0.664	0.724	-0.217	0.512	1.864
Beta upside (bond index)	0.640	0.494	0.658	0.786	-0.721	0.479	2.358
Systematic value-at-risk (decimal, weekly)	0.0003	-0.0001	-0.0002	-0.0003	-0.0020	0.0002	0.0016
Idiosyncratic value-at-risk (decimal, weekly)	-0.0318	-0.0323	-0.0328	-0.0359	-0.0414	-0.0332	-0.0272
Idiosyncratic bond volatility (percent, annual)	5.88	5.64	5.81	6.54	4.27	5.49	8.61
Idiosyncratic equity volatility (percent, annual)	27.53	31.54	30.96	33.57	19.16	31.03	44.71
Total equity volatility (percent, annual)	28.39	31.66	33.04	34.22	19.95	32.80	46.90
Bond weeks in the sample	4159	12356	69821	39501			
Individual bonds in the sample	28	113	478	334			
Individual firms in the sample	16	45	165	167			

Table III: Panel Regressions of Spreads on Systematic Risk Factors and Control Variables over 1998 to 2004

This table gives results from regressions of individual spreads on estimated risk-factor exposures and control variables. The coefficients on the factors and their associated t-statistics (in italics), calculated using robust standard errors allowing for clustering by issuer are given in the left-hand part of the table. The contributions of the factors to median spreads are given in the right-hand part of the table. Contributions are calculated as the coefficient times the range for a factor between its median and it minimum level (or zero, whichever is greater).

	Coefficients and t-statistics clustered by issuer										Contributions to Median Spreads (bps)				
Equation	**(1)**		**(2)**		**(3)**		**(4)**		**(5)**		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Beta equity			4.5	0.29								0			
Size equity			54.0	4.41								1			
Value equity			24.5	2.66								0			
Beta bond	11.4	*5.29*									5				
Size bond	27.8	*1.99*									0				
Value bond	22.6	*2.23*									0				
Beta bond with gamma					12.8	*5.94*							5		
Gamma bond					0.03	*3.64*							0		
Beta bond upside							2.7	*2.41*						1	
Beta bond downside							8.1	*6.79*						4	
Systematic VaR									-2560.6	*-5.04*					-1
Constant (AAA)	39.2	*3.5*	38.9	*3.5*	40.6	*3.5*	41.5	*3.6*	39.5	*3.5*					
Dummy AA	10.3	*1.8*	10.2	*1.8*	10.1	*1.8*	11.0	*2.0*	10.0	*1.9*					
Dummy A	31.8	*8.0*	33.2	*8.7*	31.2	*7.7*	32.2	*8.2*	32.7	*8.9*					
Dummy BBB	86.0	*14.1*	88.8	*14.9*	84.8	*13.8*	86.3	*14.2*	87.4	*14.9*					
1/Face value	1912	*2.0*	2105	*2.2*	1956	*2.0*	1909	*2.0*	1949	*2.0*	6	6	6	6	6
Coupon	3.9	*2.7*	3.9	*2.7*	3.9	*2.8*	4.1	*2.9*	4.2	*2.9*	20	20	20	21	22
Time to maturity	1.1	*5.8*	1.3	*7.4*	1.1	*5.6*	1.0	*5.4*	1.3	*7.4*	7	8	7	6	8
Dummy higher	-6.8	*-1.4*	-7.4	*-1.6*	-7.1	*-1.5*	-7.2	*-1.5*	-6.9	*-1.4*					
Dummy lower	28.7	*5.4*	28.9	*5.5*	28.3	*5.4*	28.8	*5.5*	29.0	*5.5*					
Int.rate level	0.7	*0.7*	1.0	*1.0*	0.5	*0.5*	-0.1	*-0.1*	0.9	*1.0*					
Int.rate slope	-8.8	*-11.0*	-10.1	*-11.7*	-8.7	*-11.3*	-8.9	*-10.9*	-9.2	*-11.4*					
TED (libor - tbills)	-18.9	*-6.7*	-12.7	*-4.6*	-20.8	*-7.5*	-19.3	*-6.9*	-18.9	*-6.6*					
Fin Company Dummy	8.4	*2.1*	9.6	*2.4*	8.1	*2.0*	8.5	*2.1*	9.0	*2.2*					
N	125837		125837		125837		125837		125837						
R-squared	0.313		0.314		0.316		0.315		0.311						

Table IV: Panel Regressions Relating Spreads to Idiosyncratic Factors and Control Variables over 1998 to 2004

This table presents the results of regressions of individual spreads on idiosyncratic factors and control variables. The coefficients on the factors and their associated t-statistics (in italics), calculated using robust standard errors allowing for clustering by issuer are given in the left-hand part of the table. The contributions of the factors to median spreads are given in the right-hand part of the table. Contributions are calculated as the coefficient times the range for a factor between its median and it minimum level (or zero, whichever is greater).

Coefficients and t-statistics clustered by issuer

Equation	(6)		(7)		(8)		(9)		(6a)		(7a)		(8a)		(9a)	
Equity volatility	2.0	*9.62*			1.2	*6.98*			2.4	*13.49*			1.7	*10.28*		
S&P volatility	0.8	*5.86*	0.8	*6.18*	0.6	*4.67*	1.0	*7.87*	1.2	*9.18*	1.6	*12.58*	0.9	*7.32*	1.6	*13.83*
Bond volatility			15.4	*11.31*	13.0	*9.30*					15.1	*16.45*	12.6	*13.42*		
Idiosync. VAR							-2466.8	*-9.50*							-3186.7	*-13.71*
S&P return	-186.5	*-11.59*	-217.5	*-17.90*	-183.6	*-12.96*	-228.7	*-17.40*	-134.6	*-7.53*	-153.3	*-10.81*	-138.6	*-8.81*	-160.3	*-10.41*
Constant (AAA)	-61.0	*-5.13*	-31.2	*-3.00*	-53.9	*-5.28*	-44.8	*-3.88*	-25.4	*-3.12*	-54.4	*-8.38*	-76.0	*-10.60*	-63.5	*-7.82*
Dummy AA	3.7	*0.81*	3.6	*1.02*	1.7	*0.49*	6.1	*1.41*	-3.5	*-0.61*	9.9	*2.61*	3.6	*0.99*	3.2	*0.71*
Dummy A	27.7	*6.39*	28.4	*9.98*	25.4	*7.99*	31.1	*8.88*	23.9	*4.28*	32.6	*9.52*	26.5	*7.35*	28.1	*9.35*
Dummy BBB	79.3	*12.89*	73.6	*16.03*	69.9	*14.57*	81.3	*15.36*	73.2	*9.92*	78.6	*14.72*	70.7	*13.15*	74.5	*13.63*
1/face value	3035.7	*3.02*	2304.9	*2.85*	2614.5	*3.17*	2116.1	*2.33*	3480.6	*3.19*	3111.3	*3.76*	3116.5	*3.63*	2460.0	*2.49*
Coupon	3.9	*2.71*	-1.3	*-1.05*	-0.3	*-0.20*	-2.7	*-1.74*								
Time to maturity	1.5	*7.81*	-0.5	*-2.28*	-0.2	*-0.90*	1.1	*6.70*								
Dummy higher	-8.0	*-2.42*	-4.9	*-1.61*	-6.2	*-2.14*	-4.8	*-1.57*								
Dummy lower	21.3	*4.64*	16.8	*4.60*	14.6	*3.94*	22.9	*5.64*								
Int.rate level	2.4	*2.07*	5.4	*5.69*	2.3	*2.21*	6.2	*6.37*								
Int.rate slope	-2.2	*-2.54*	-5.6	*-7.21*	-3.7	*-4.68*	-4.0	*-4.80*								
TED (libor - tbills)	-0.4	*-0.17*	-1.3	*-0.66*	1.4	*0.65*	-3.5	*-1.60*								
Fin Comp Dummy	13.4	*3.20*	7.6	*2.35*	10.3	*3.03*	8.6	*2.40*	4.7	*1.03*	8.4	*2.52*	10.8	*2.98*	2.2	*0.60*
N	125837		125837		125837		125837		125837		125837		125837		125837	
R-squared	0.478		0.519		0.538		0.470		0.418		0.475		0.523		0.410	

Contributions to Median Spreads (bps)

Equation	(6)	(7)	(8)	(9)	(6a)	(7a)	(8a)	(9a)
Equity volatility	42		27		52		37	
S&P volatility	7	7	5	9	11	14	8	15
Bond volatility		66	56			65	54	
Idiosync. VAR				65				84
	50	73	88	74	63	79	99	99
1/face value	9	7	8	6	10	9	9	7
Dummy higher	59	80	96	81	73	88	108	106

Table V: Idiosyncratic Bond-Volatility Deciles and Estimated Liquidity Premia

This table gives information on bond-volatility deciles. The mean bond volatility in column 2 for each decile is in percent per annum. The coefficient on 1/ face-value of issue (column 3) is estimated with a panel regression of bond spreads on: ratings, equity volatility, S&P volatility, S&P return and 1/ face-value by decile. The liquidity premia in column 5 are the result of dividing the numbers in column 3 by those in column 4 and rounding to the nearest basis point

(1) Idiosyncratic Bond Volatility Decile	(2) Mean Idiosyncratic Bond Volatility	(3) Coefficient on 1/Face-Value	(4) Mean Face-Value of Bond Issue $m	(5) Liquidity Premium in basis points
1	3.77	471	301	2
2	4.46	998	290	3
3	4.76	1740	287	6
4	5.03	2053	296	7
5	5.33	3330	286	12
6	5.68	4202	278	15
7	6.17	4867	303	16
8	6.90	4927	295	17
9	7.93	6042	287	21
10	10.22	5944	270	22

Table VI: Results from Calibrating a Merton-style Model to the Spread/Equity-Volatility Sensitivities for Leverage Deciles

This table presents the results of calibrating a Merton-style structural model for each leverage decile to the estimated sensitivity of the spread to equity volatility for that leverage decile. Median values for leverage are used in this exercise, as we wish to generate representative implied volatilities for each decile. Only non-financial companies are included, as leverage measures for financial companies can be misleading.

Leverage Decile (1)	Median Leverage (2)	Median Duration (3)	Regression Slope on Equity Volatility (4)	Implied Firm-Value Volatility (%) (5)	Implied Equity Volatility (%) (6)	Model Spread (bp) (7)	Median Market Spread (bp) (8)
1	0.055	6.11	2.57	46.9	49.6	14.8	75
2	0.110	6.51	2.62	37.1	41.6	14.1	79
3	0.152	6.38	2.88	33.7	39.7	15.8	97
4	0.198	5.66	3.04	31.8	39.5	17.3	105
5	0.250	6.58	2.91	26.5	35.2	15.9	115
6	0.299	5.95	2.98	24.9	35.3	16.7	129
7	0.355	6.96	3.30	21.8	33.6	20.3	137
8	0.416	6.00	3.20	20.3	34.5	20.8	129
9	0.480	6.23	3.29	18.0	34.2	23.2	148
10	0.612	6.26	4.11	16.4	40.9	49.9	155

Table VII: Panel Regressions Relating Spreads to Idiosyncratic Factors and Control Variables for 2005-2006

This table gives results from regressions of individual spreads on estimated risk-factor exposures and control variables. The coefficients on the factors and their associated t-statistics (in italics), calculated using robust standard errors allowing for clustering by issuer are given in the left-hand part of the table. The contributions of the factors to median spreads are given in the right-hand part of the table. Contributions are calculated as the coefficient times the range for a factor between its median and it minimum level (or zero, whichever is greater).

Coefficients and t-statistics clustered by issuer

Equation	(10)		(11)		(12)		(13)		(10a)		(11a)		(12a)		(13a)	
Equity volatility	0.1	*5.12*			0.1	*5.15*			0.0	*1.16*			0.1	*2.53*		
S&P volatility	-0.2	*-1.31*	-0.1	*-0.96*	-0.1	*-0.91*	-0.1	*-1.13*	-0.4	*-2.21*	-0.3	*-3.43*	-0.3	*-3.39*	-0.3	*-2.30*
Bond volatility			17.7	*42.69*	17.7	*42.74*					18.9	*117.91*	18.9	*117.93*		
Idiosync. VAR							-809.5	*-14.03*							-1727.1	*-86.46*
S&P return	-52.6	*-5.34*	-50.5	*-5.80*	-49.7	*-5.71*	-53.4	*-5.55*	-62.3	*-4.65*	-73.6	*-8.14*	-73.1	*-8.07*	-64.5	*-5.58*
Constant (AAA)	33.6	*9.58*	14.4	*4.83*	13.1	*4.35*	31.6	*9.56*	65.1	*34.27*	-7.0	*-5.51*	-7.9	*-6.12*	21.5	*13.70*
Dummy AA	6.7	*18.64*	5.8	*17.32*	5.6	*16.68*	6.5	*18.24*	6.5	*15.04*	6.3	*18.54*	6.2	*18.14*	6.3	*17.21*
Dummy A	14.6	*39.41*	13.7	*40.00*	13.5	*38.32*	14.3	*40.17*	16.3	*35.02*	12.6	*37.94*	12.4	*37.13*	13.6	*34.70*
Dummy BBB	45.3	*58.97*	39.9	*59.37*	39.5	*60.40*	44.9	*57.98*	50.2	*53.59*	36.5	*50.20*	36.2	*52.14*	44.2	*49.87*
1/face value	-772.6	*-10.44*	-972.2	*-15.17*	-965.8	*-15.23*	-777.9	*-10.50*	858.4	*8.56*	-1192.1	*-17.35*	-1188.4	*-17.40*	-112.8	*-1.27*
Coupon	3.4	*52.06*	-4.9	*-25.31*	-4.9	*-25.36*	0.6	*2.86*								
Time to maturity	2.3	*61.70*	1.5	*40.80*	1.5	*40.79*	2.4	*59.94*								
Dummy higher	-5.1	*-9.36*	-4.0	*-8.18*	-4.2	*-8.47*	-5.0	*-9.23*								
Dummy lower	15.1	*16.37*	12.9	*15.83*	12.8	*15.45*	15.4	*16.87*								
Int.rate level	-2.8	*-3.99*	-1.7	*-2.91*	-1.7	*-2.90*	-3.2	*-4.62*								
Int.rate slope	-2.3	*-3.54*	-3.2	*-5.82*	-3.2	*-5.65*	-1.6	*-2.44*								
TED (libor - tbills)	9.9	*4.03*	12.0	*5.14*	11.9	*5.20*	9.6	*3.86*								
Fin Company Dum	1.7	*4.17*	0.9	*2.54*	1.1	*2.97*	1.0	*2.67*	-10.4	*-15.60*	-0.6	*-1.47*	-0.5	*-1.12*	-6.7	*13.70*
N	70509		70509		70509		70509		70509		70509		70509		70509	
R-squared	0.610		0.663		0.664		0.613		0.281		0.547		0.548		0.352	

Contributions to Median Spreads (bps)

Equation	(10)	(11)	(12)	(13)	(10a)	(11a)	(12a)	(13a)
Equity volatility	1		1		0		0	
S&P volatility	0	0	0	0	-1	-1	-1	-1
Bond volatility		47	47			50	50	
Idiosync. VAR				18				38
	0	47	48	17	-1	49	50	37
1/face value	-3	-4	-4	-3	3	-5	-5	0
	-3	43	44	15	2	45	45	37

Table VIII: Panel Regressions Relating Spreads to Idiosyncratic Factors and Control Variables for 2007-2009

This table gives results from regressions of individual spreads on estimated risk-factor exposures and control variables. The coefficients on the factors and their associated t-statistics (in italics), calculated using robust standard errors allowing for clustering by issuer are given in the left-hand part of the table. The contributions of the factors to median spreads are given in the right-hand part of the table. Contributions are calculated as the coefficient times the range for a factor between its median and it minimum level (or zero, whichever is greater).

	Coefficients and t-statistics clustered by issuer																Contributions to Median Spreads (bps)							
Equation	**(14)**		**(15)**		**(16)**		**(17)**		**(14a)**		**(15a)**		**(16a)**		**(17a)**		**(14)**	**(15)**	**(16)**	**(17)**	**(14a)**	**(15a)**	**(16a)**	**(17a)**
Equity volatility	1.5	*4.13*			1.0	*3.10*			2.5	*7.19*			1.4	*4.55*			34		23		57		32	
S&P volatility	2.8	*5.88*	1.7	*5.97*	1.2	*3.41*	2.1	*7.05*	4.5	*6.38*	3.9	*15.28*	3.0	*7.55*	4.8	*17.27*	38	23	17	28	61	53	41	65
Bond volatility			14.0	*9.73*	12.9	*9.12*					15.6	*16.19*	12.5	*10.23*				52	48			58	46	
Idiosync. VAR							-3073.0	*-8.23*							-3633.0	*-11.39*				94				111
																	72	75	88	121	118	111	119	175
S&P return	-384.1	*-13.29*	-477.0	*-14.19*	-477.6	*-14.33*	-429.0	*-13.56*	-331.3	*-8.10*	-443.7	*-13.63*	-470.1	*-14.08*	-351.6	*-10.32*								
Constant (AAA)	19.3	*0.77*	43.5	*2.06*	30.9	*1.43*	28.5	*1.32*	-105.8	*-6.51*	-109.0	*-8.59*	-104.7	*12.54*	-149.0	*-10.03*								
Dummy AA	-7.1	*-0.99*	9.9	*1.38*	-0.9	*-0.12*	16.3	*2.35*	-4.3	*-0.60*	17.5	*3.19*	0.6	*0.09*	27.4	*4.90*								
Dummy A	56.4	*6.12*	65.0	*7.97*	50.5	*7.01*	75.6	*8.27*	63.9	*5.40*	77.2	*9.76*	54.2	*6.91*	92.5	*9.69*								
Dummy BBB	168.8	*11.49*	152.4	*12.33*	139.3	*11.02*	164.9	*12.46*	183.9	*12.27*	165.1	*12.77*	145.7	*11.69*	180.4	*12.65*								
1/face value	11842.0	*4.41*	7008.0	*2.95*	9824.0	*4.49*	4612.0	*1.89*	10987.0	*3.55*	2720.0	*1.14*	8162.0	*3.57*	-1146.0	*-0.45*	19	11	16	8	18	4	13	-2
Coupon	3.4	*1.61*	-1.9	*-0.83*	-1.5	*-0.70*	-4.5	*-1.97*																
Time to maturity	0.0	*0.04*	-2.0	*-2.41*	-1.9	*-2.25*	-1.2	*-2.23*																
Dummy higher	4.9	*0.91*	-10.4	*-2.37*	-5.8	*-0.97*	-8.6	*-2.08*									92	86	104	129	136	115	132	174
Dummy lower	65.0	*5.88*	55.8	*4.38*	44.0	*4.14*	54.5	*4.26*																
Int.rate level	-29.5	*-6.91*	-24.6	*-6.99*	-22.7	*-5.58*	-27.0	*-7.91*																
Int.rate slope	6.9	*2.84*	-0.5	*-0.22*	-6.0	*-2.22*	8.1	*4.45*																
TED (libor - tbills)	2.3	*4.42*	18.7	*4.46*	23.9	*4.92*	11.2	*2.96*																
Fin Company Dum.	87.8	*8.73*	74.2	*9.94*	66.1	*8.21*	73.9	*9.63*	85.5	*7.60*	93.5	*10.66*	80.7	*9.99*	90.2	*10.99*								
N	92649		92649		92649		92649		92649		92649		92649		92649									
R-squared	0.602		0.642		0.65		0.651		0.572		0.615		0.635		0.614									

Figure 1: Average Credit Spreads by Rating and S&P500 Level over the 1998-2004 Period
The data in this figure are weekly and relate to the period from 7th January 1998 to 29th December 2004. The credit spreads are in basis points and relate to the left-hand axis. The S&P500 level relates to the right-hand axis.

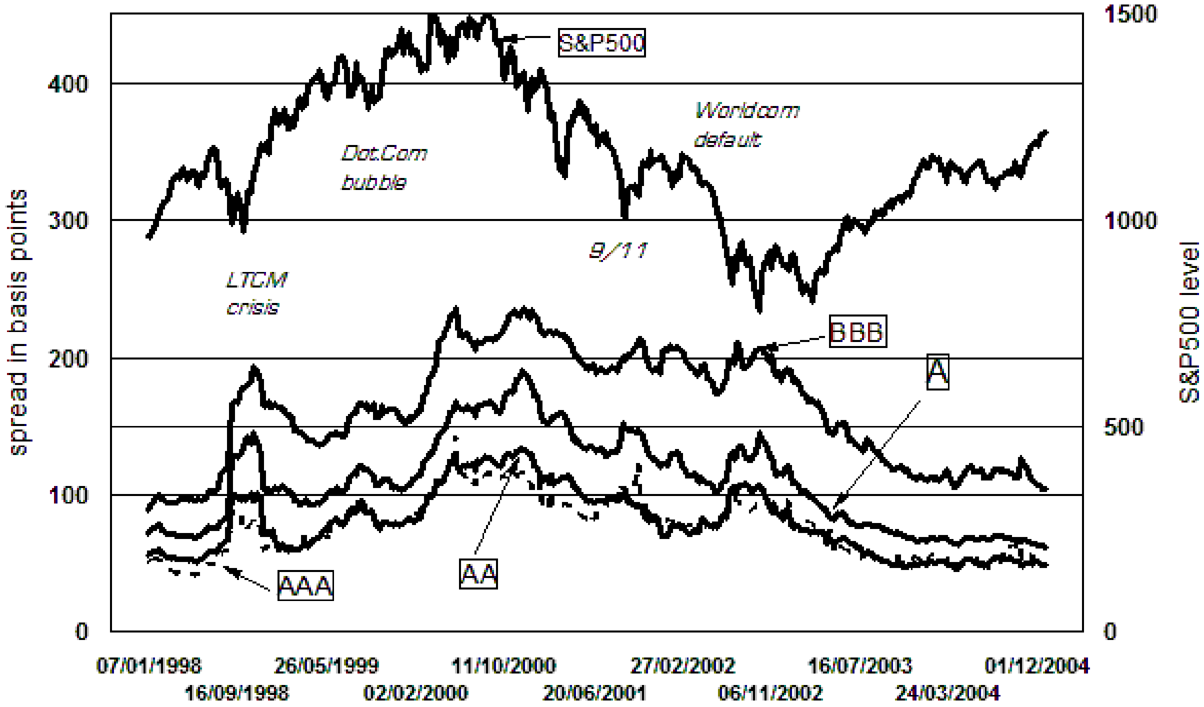
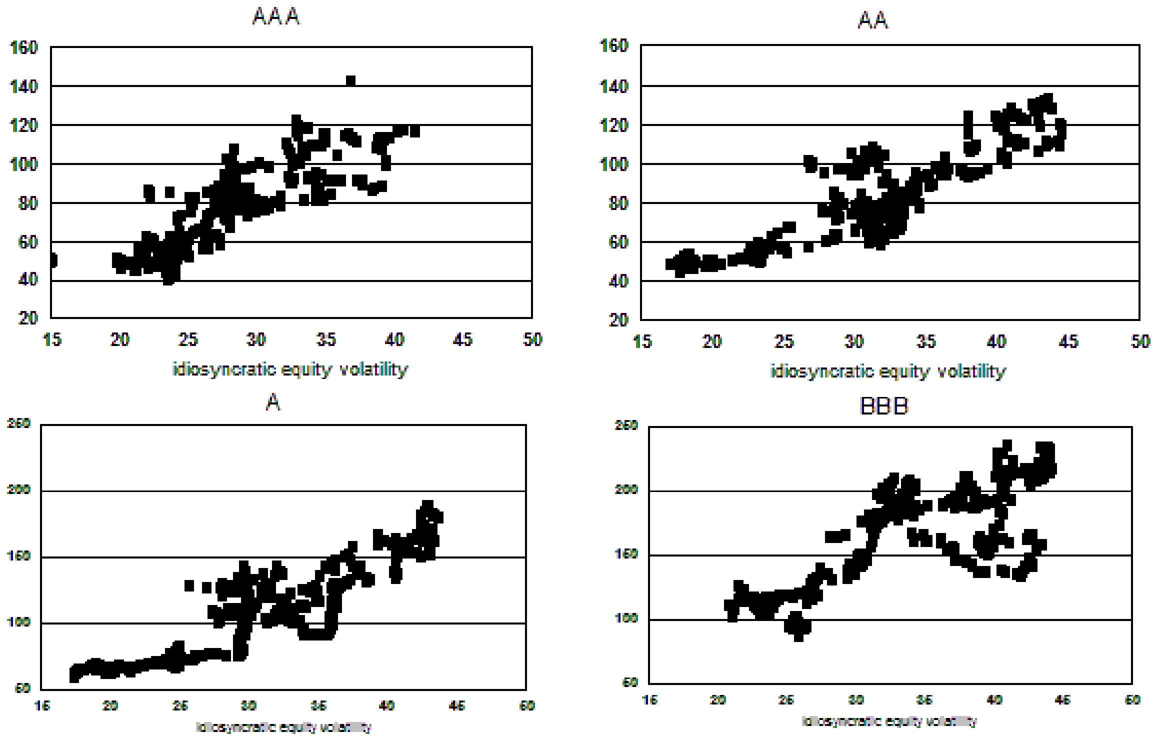


Figure 2: Credit Spreads and Idiosyncratic Volatilities, averaged by week and rating, for 1998 to 2004

Each point in a graph is the result of averaging across all bonds in a particular rating category in a particular week. There are 365 weeks in the sample. The y-axis is the credit spread in basis points. The x-axis in Panel A is idiosyncratic equity volatility and the x-axis in Panel B is idiosyncratic bond volatility.

Panel A: Equity Idiosyncratic Volatilities and Spreads by Rating



Panel B: Bond Idiosyncratic Volatilities and Spreads by Rating

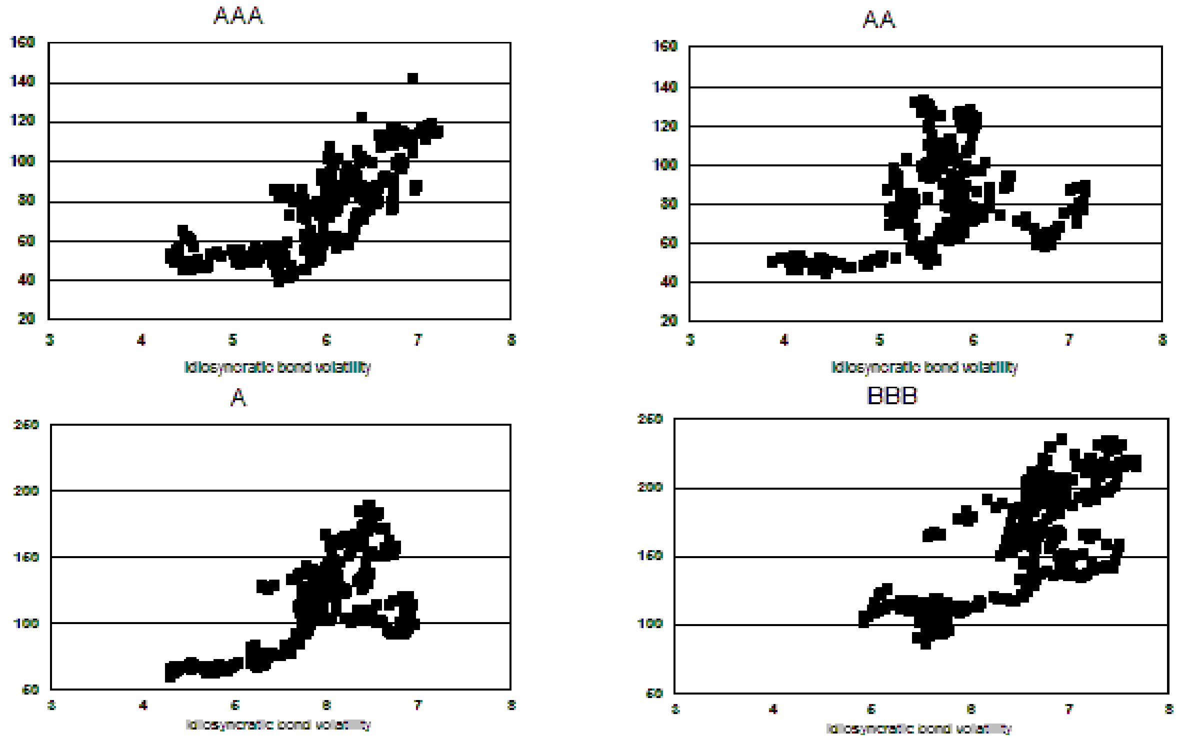


Figure 3: Implied Volatility and Leverage (for leverage deciles) from Merton Model

This graph gives implied volatilities for firm-value (lower line) and equity (upper line) against leverage for each of the leverage deciles. The values for the plots are given in Table VI.

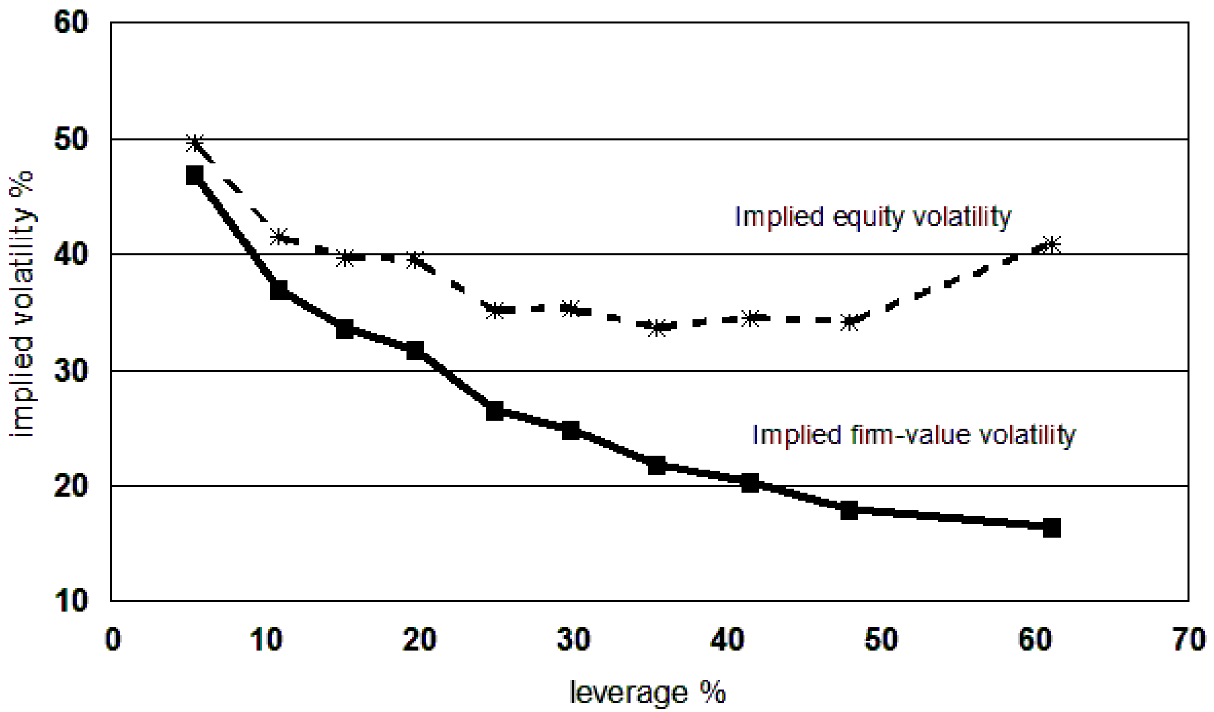


Figure 4: A-Bond Spreads and S&P500 Volatility over 1998-2009

This graph gives the average spread in each week for the bonds in the sample which are A-rated, together with the S&P500 volatility at that time. The volatility is measured as an exponentially-weighted moving average over the last 180 days.